An Improved Disability-Based Medicare Payment System For The Social/HMO

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1. Introduction

a. Overview

Most Medicare cost models are very poor in terms of their explanatory power. In order for capitation formulas to be truly sensitive to the composition of the relevant populations these formulas need to be based on a typology that differentiates these populations into meaningful categories in relation to cost. Research on the factors that underlie this typology have taken several directions, although most of these approaches are based on variants of demographic and health status measures. In this study, we attempt to evaluate the advantages and disadvantages of particular Medicare payment models for use in the Social/HMO demonstration program using various definitions of health status. In evaluating these models attention is paid not only to the efficiency of models, but also to the implementation issues and policy implications of such models.

A basic assumption underlying the current study is that a disability-based modification of the HCFA's accepted method for setting capitation rates for HMOs is appropriate for the Social/HMO demonstration. The study seeks to identify the most appropriate method for identifying high-cost subgroups of the population, based upon the type and severity of functional limitations.

b. Objectives

The goal of this study is to develop an improved payment model that can be used by the Health Care Financing Administration in setting capitation rates for organizations that participate in the Social/HMO demonstration program. Several alternative models are explored, including

- a model that uses nursing home certifiability

- a model that uses limitations in activities of daily living, and

- a model that uses limitations in activities of daily living and in instrumental activities of daily living,

and the advantages and disadvantages of each are analyzed.

Specific objectives are as follows:

(1) To analyze Medicare expenditures in relationship to demographic and functional status measures, including nursing home certifiability, ADL and IADL limitations and cognitive

functioning.

(2) To develop predictive models of Nursing Home Certifiability using S/HMO data.

(3) To develop several alternative capitation models using functional status, and

(4) To analyze the advantages and disadvantages of these alternative payment models.

2. Review of Methods Currently Used by Medicare to Establish Capitation Rates for the Social/HMO and PACE demonstrations

The development of a disability-adjusted capitation payment formulas for Medicare has proceeded in several phases. These are discussed below.

a. Payment formula used for the Social/HMO

The current payment formula used in the S/HMO demonstration is a simple modification of the Average Adjusted Per Capita Cost (known as the AAPCC) formula used by Medicare in establishing payment rates for HMOs enrolling Medicare recipients under TEFRA. The AAPCC is essentially a table of relative cost factors (Kunkel and Powell, 1981) or underwriting ratios (defined as the ratio between per capita costs of a subgroup of persons divided by the average per capita costs of all elderly during that year) that establish different payment rates for groups of individuals based upon their relative risk. This table takes into account four variables: age, gender, whether the individuals resides in the community or in a long-term care institution, and whether the individual is eligible for Medicaid. Separate tables are used for Part A and Part B services. The AAPCC tables - adjusted annually to take into account shifts in the demographic composition of the elderly population - were used to set rates for TEFRA HMOs and were originally derived by pooling data from 1974, 1975 and 1976 surveys conducted by Medicare (called the Current Medicare Survey or CMS) for a sample of Medicare recipients are shown in Table 1 below.

When the Social/HMO program was first implemented, it was noticed that the AAPCC formula was inappropriate to use for setting capitation rates because this formula establishes incentives that are counter to an important objective of the program. In particular, the AAPCC rate cells display payment rates for persons residing in nursing homes that are approximately two times higher than for the average Medicare recipient. However, the AAPCC tables do not

Table 1: The AAPCC: Demographic Cost Factors for 1993 Used to Establish Medicare Payment Rates to TEFRA HMOs

Age Group	Institutionalized	Non-Institutionalized Medicaid	Non-Institutionalized Non-Medicaid
Part A			
Male			
65-69	1.90	1.30	.70
70-74	2.40	1.70	.85
75-79	2.40	2.10	1.10
80-84	2.40	2.35	1.20
85 & over	2.40	2.50	1.30
Female			
65-69	1.55	.85	.55
70-74	1.80	1.10	.70
75-79	2.00	1.40	.80
80-84	2.00	1.85	1.00
85 & over	2.00	1.95	1.10
Part B			
Male			
65-69	1.80	1.10	.75
70-74	1.85	1.40	1.00
75-79	1.90	1.60	1.10
80-84	1.90	1.65	1.15
85 & over	1.90	1.65	1.15
Female			
65-69	1.50	1.10	.75
70-74	1.65	1.15	.85
75-79	1.70	1.25	.95
80-84	1.70	1.25	1.00
85 & over	1.70	1.25	1.00

recognize the higher average costs that are likely to be encountered by frail persons who reside in the community who may pose the same level of risk to the Medicare program as do the individuals who reside in nursing homes.

The consequences of using this kind of payment formula are as follows: a participating organization operating under this formula (e.g., Social/HMO) would receive a higher payment amount from the Medicare program if they were to refer a frail individual residing in the community for placement in a nursing home.

In order to remove this perverse incentive, a modified payment formula was sought that would adjust for the health status of individuals residing in the community. Existing national data sources (the 1977 Current Medicare Survey [CMS], a survey carried out annually by the Medicare program from 1965 to 1977) were used to demonstrate that functionally limited elders residing in the community had higher Medicare costs than individuals who were not so limited. However, the available data did not appear sufficient to establish a payment formula. Instead, a new formula was developed using the following plausible approach.

The new approach singles out frail individuals who reside in the community whose disabilities are so severe that they would be regarded by trained clinicians to be in need of daily assistance from another person, and who would be found by state public health or welfare officials to be certifiable for public payment under Medicaid in nursing facilities or under community-based waiver programs. These individuals are referred to as "nursing home certifiable" or "NHC". In the absence of adequate empirical data, it was simple <u>assumed</u> that these individuals would have the same per-capita Medicare costs as those experienced by individuals who reside in long-term care facilities.

A new AAPCC rate table was created for the Social/HMO program by adding an additional column which pertained to persons residing in the community who are NHC. The underwriting ratios used for these new subgroups of persons were the same as the ratios found in the corresponding row (i.e., for persons having the same age and gender) in the "Institutional" column.) The modified AAPCC table used for the AAPCC for the S/HMO is shown in Table 2 below.

It should be noted that the persons represented by the columns entitled "Community non-welfare" and "Community welfare" differ between Table 1 and 2. In Table 2, these subgroups do not include the frail individuals identified to be "NHC" - they are separately contained in the NHC column. The remaining persons

Table 2: The Modified AAPCC: Demographic Cost Factors for 1993 Used to Establish Medicare Payment Rates for the Social HMO

Age Group	Institutionalized or NHC in Community	Non-Institutionalized Medicaid	Non-Institutionalized Non-Medicaid
Part A			
Male			
65-69	1.90	1.27	.67
70-74	2.40	1.65	.80
75-79	2.40	2.07	1.05
80-84	2.40	2.34	1.14
85 & over	2.40	2.51	1.23
Female			
65-69	1.55	.80	.53
70-74	1.80	1.02	.65
75-79	2.00	1.20	.72
80-84	2.00	1.57	.90
85 & over	2.00	1.94	.97
Part B			
Male			
65-69	1.80	1.08	.73
70-74	1.85	1.37	.97
75-79	1.90	1.57	1.07
80-84	1.90	1.62	1.11
85 & over	1.90	1.62	1.10
Female			
65-69	1.50	1.02	.69
70-74	1.65	1.09	.82
75-79	1.70	1.18	.90
80-84	1.70	1.18	.93
85 & over	1.70	1.12	.90

are thus healthier than the corresponding persons in Table 1. To assure that there would be a fair accounting for frail and non-frail persons, the underwriting factors in Table 2 in the Community non-welfare and non-welfare columns were reduced (as can be seen by comparing Tables 1 and 2) to take account of this separation. This reduction was carried out by partitioning the community and welfare cells in Table 1 into "well" and "NHC" components. To do this required having estimates of the number of persons who are NHC by age and sex among the Medicare population. These estimates were made using data from the CMS.

b. Payment formula used for the PACE demonstration

In the PACE demonstration, individuals who are NHC enroll in a special program that encompasses a full range of acute and long-term health and social services. Services include those covered by Medicare and Medicaid, including long-term institutional care if necessary. The PACE program relies heavily on an adult day health model developed over a number of years by On Lok Senior Health Services in San Francisco, California.

The PACE programs rely upon capitation-based financing with contributions coming from Medicare and Medicaid as well as from individuals who are not eligible for Medicaid. After the modified AAPCC was developed for the Social/HMO demonstration, the On Lok program began to receive capitation payments from HCFA that were based upon the NHC-adjusted AAPCC shown in Table 2. After some time, an examination of acute care utilization and costs experienced in various long-term care demonstrations was undertaken by On Lok. Although data were rather sketchy, the analysis suggested that Medicare cost ratios for frail elderly residing in the community may be considerably higher than those shown in Table 2. On the basis of this analysis, On Lok and HCFA agreed to a somewhat augmented capitation rate for On Lok members that was set equal to 2.39 times the average per capita Medicare capita costs (for Parts A and B combined). This rate is currently in effect for each of the sites participating in the PACE demonstration.

In 1989 a HCFA-sponsored study (Gruenberg, et. al., 1990) undertook to provide a firmer empirical basis for establishing capitation rates for the PACE demonstration. Using data from the National Long-Term Care survey linked with Medicare data, a range of estimates was made. The best estimate for the cost ratio for the NHC population was found to be equal to 2.42. This analysis provided support for the notion that the NHC population had higher Medicare costs than did nursing home residents.

3. Overview of methodology

a. Sources of Data

(1) 1984 National Long-Term Care Survey

The primary source of data used was the 1984 National Long-Term Care Survey (NLTCS). This survey provides detailed self-reported data regarding the health and functional status of the U.S. elderly population. Moreover, these data have been linked to actual Medicare records by the Health Care Financing Administration. This linkage enabled us to analyze the actual Medicare costs of persons 65 and over in relationship to their functional status.

We used data from the detailed portion of NLTCS to classify individuals according to their functional status. This detailed survey was carried out for the subsample of persons who were found to have one or more limitations in activities of daily living (ADL) or instrumental activities of daily living (IADL) for a period of 90 or more days. Medicare costs were aggregated for a period of 1 year beginning with the date of the screener survey.

In analyzing these data, we used a version of the NLTCS tape that had been developed at the Agency for Health Care Policy and Research (AHCPR). Specifically, we used the cross-sectional sample weights (called nlivwt84 in the AHCPR documentation) developed by AHCPR in carrying out our cost analyses.

(2) Social/HMO health status form and NHC data

The NLTCS did not include any determination of whether a surveyed individuals would be judged as NHC. This judgment would have required a clinical evaluation of persons included in the survey.

We obtained data from four States where decisions regarding nursing home certifiability were made for a sample of 13032 persons, and for whom detailed survey data collected on a health status form (HSF) similar to that found in NLTCS were collected. These data were collected for each person enrolled as a member at one of the four sites participating in the Social/HMO demonstration. We used these data in conjunction with a second data set from each site indicating the first date (if any) that the enrollee was found to be NHC. These NHC determinations are made at each site as a part of detailed assessments using a comprehensive assessment form (CAF). We didn't need to use detailed data from the CAF, but we did rely on the date the CAF was completed.

b. Determining Nursing Home Certifiability

Models to predict the probability that an individual would be clinically evaluated as NHC were constructed using logit analysis. The dependent variable was the persons's clinically-determined NHC status. The independent variables were the self-reported items on the HSF.

c. Medicare cost analysis

In analyzing the relationship between Medicare costs and individual characteristics, we employed multiple regression analysis. This method has been the standard one used (Beebe, et. al., 1985; Ash, et. al., 1989) in other studies of the AAPCC, (because it yields a mean value of Medicare costs exactly equal to the observed mean) although there are problems associated with the distribution of values of the dependent variable (i.e., costs), because many persons have no Medicare costs in any one year (Tobin, 1958; Duan, et. al., 1983).

4. Models for predicting nursing home certifiability

We based our analysis upon work our previous work (Gruenberg, et. al., 1990). Our objectives in extending this analysis were as follows:

(1) To improve the model building and testing of predictive NHC models, using Social/HMO data. Improvements sought were as follows:

(a) Expand the S/HMO data base from what was used before so as to have a larger number of cases to work with, so that site-specific models for NHC would be possible. It would be important to determine whether different models for NHC that are in effect in different States would lead to different Medicare S/HMO payment rates, if "NHC" status is used in the payment formula. For this reason, it was felt that it would be important to expand the number of cases.

(b) Sharpen the predictive models by including more variables. In the earlier analysis, we had used demographic and ADL/IADL variables. We wanted to determine whether the fit could be improved by including additional variables.

(c) Employ more refined methods for testing the goodness of fit of the predictive NHC models. In our earlier work for the PACE demonstration, it was suggested that we use a more sensitive method to check these models.

We obtained health status form (HSF) data that included data for all new members whose enrolled and whose first HSF was completed prior to December 31, 1987. In our earlier work (Gruenberg, et. al., 1990), we only had data through September, 1986. The data used for the current study included 13,032 S/HMO members compared with 8,464 members we had available for the earlier study. study.

We found that altogether 1760 persons had positive NHC determinations at some point in time. This represents more than 13% of all enrollees. However, only 20% (366 out of 760) of the persons found to be NHC had this determination made within 40 days of their HSF. Among the sites, only Kaiser had more than 100 persons NHC within 40 days, as is shown in Table 3 below.

Table 3: Nursing Home Certifiability (NHC) by Site by Time Between HSF and NHC Determination

SITE	TOTAL NON NHC	NHC OUTSIDE 40 DAYS	NHC WITHIN 40 DAYS	TOTAL
ELDER PLAN	4446	124	80	4650
	95.61	2.67	1.72	100.00
	39.44	8.90	21.86	35.68
KAISER	4247	877	208	5332
	79.65	16.45	3.90	100.00
	37.68	62.91	56.83	40.91
SENIORS PLUS	1818	244	22	2084
	87.24	11.71	1.06	100.00
	16.13	17.50	6.01	15.99
SCAN	761	149	56	966
	78.78	15.42	5.80	100.00
	6.75	10.69	15.30	7.41
TOTAL	11272	1394	366	13032
	86.49	10.70	2.81	100.00
	100.00	100.00	100.00	100.00

In spite of the larger number of cases that we had, compared with our earlier study, we found that there were not a sufficient number of persons found to be "NHC" to develop site-specific models when the 40-day limit is used, except for the Kaiser-Portland site.

We used logit analysis to estimate the probability that a person having a particular constellation of health conditions was found to be NHC. In developing this model we eliminated variables on a reverse step-wise basis, if they were not found to be significant at the .05 level. Variables were eliminated one at a time, beginning with the variable that was found to have the lowest significance level.

According to the logit analysis, the probability of being NHC is given by the following formula:

Equation 1: $$\text{Probability} = \frac{e^F}{(1+e^F)}$$

where the F is a linear function of the independent variables. F was taken to be a linear combination of the independent variables x_i:

Equation 2: $$F(x) = a_0 + a_1x_1 + a_2x_2 + \quad \ldots\ldots\ldots$$

and the coefficients a_i were determined using a maximum likelihood method. We used the logit procedure in the Stata, Version 3 statistical package (Computing Resource Center, 1992) to carry this out.

Persons were classified to be NHC or non-NHC according to clinical records obtained from the Social/HMO data system. However, individuals who were found to be NHC more than 40 days after the time of their HSF were identified and separate analyses were carried out with them and without them. Our earlier study (Gruenberg, et. al., 1990) had shown that for these persons, there was poor agreement between data on the HSF and data collected as a part of the clinical determination of NHC on a comprehensive assessment form (CAF). We may presume that these persons developed health and functional problems after the time of completing their HSF that led to their being judged to be NHC. For this reason, it may not be appropriate to use the health status data on the HSF to determine whether they were NHC.

In developing a model predicting NHC status, we were primarily interested in using the model to predict who was NHC among the NLTCS population. For this reason, we selected variables that were available, with similar definitions on both the HSF and the NLTCS. We developed two types of models: one using a comprehensive set of health and functional status variables, and, a second using a more limited set of ADL and IADL variables. We also developed a site-specific model for the one

site (Portland, Oregon) where sufficient data were available when the 40-day limitation was used.

To proceed with the analysis, a subdivision of the data was made: the population surveyed on the HSF was divided into "frail" and "non-frail" subgroups. The non-frail component was discarded, and the predictive model was used to estimate the NHC probability for those who were frail. This step was undertaken in order to match the process used in carrying out the National Long-Term Care Survey. The NLTCS was a two-stage sample, with detailed health status information collected only for the subsample of persons who were determined from the first stage to be frail.

The definitions used in subdividing the population into frail/non-frail components were chosen to match, as closely as possible, the definitions used to trigger the detailed survey in the NLTCS. Persons were regarded as frail unless all of the following was true:

- They did not need the help of another person in personal care activities (ADL) including bathing, dressing, transferring, toileting or feeding (included were persons who reported they needed help at least some of the time);
- They did not need the help of another person in instrumental activities (IADL) including grocery shopping, meal preparation, household chores, doing laundry, managing money, taking medications, and making telephone calls;
- They were able to get around inside and outside the house without the help of another person

Altogether, we examined two sets of NHC logit models; within each set there were three models. In the first set (Models 1-3, which we will call the ADL/IADL models), we used a limited number of variables including an index of ADL, individual IADL variables, mobility limitations, age sex, and the number of hospitalizations in the past 12 months. In the second set (Models 4-6 which we will call the unrestricted health status models) we expanded the number of independent variables. We included other variables that were in common on the HSF and on the National Long-Term Care Survey. These included: self-reported health status, diagnoses (cancer and/or diabetes), whether the person has an ostomy or a catheter, and the use of certain equipment (cane, walker, hoyer lift, grab-bars or a bathing bench.)

For each of these two sets of models we tested the following three models:

- a pooled model, using data from all sites and including all

persons found to be NHC, even if the time between NHC determination and HSF was greater than 40 days (Models 1 & 4).

- a pooled model, using data from all sites but including data for persons found to be NHC within 40 days of their HSF. In this model, we dropped the cases for whom NHC determinations occurred after 40 days (Models 2 & 5).

- a Kaiser-only model, including only persons whose NHC determination occurred within 40 days. As in the model described above, we dropped the cases form whom NHC determinations occurred after 40 days (Models 3 & 6).

Table 4 shows the results of the logit analysis. This table gives the coefficients of the independent variables in Equation 2.

Table 4: Logit Models for Predicting NHC Status

a. ADL/IADL Models

	POOLED DATA				PORTLAND ONLY	
			< 40 days from HSF to NHC			
	(MODEL 1)		(MODEL 2)		(MODEL 3)	
VARIABLE	COEFFICIENT	t	COEFFICIENT	t	COEFICIENT	t
age	.046	6.876	.022	1.939	.056	3.297
adlscore	.438	9.768	.722	12.781	1.005	9.218
shop					.454	1.436
meals	.176	1.411	.315	1.318		
money	.229	1.838			.582	1.740
laundry			.316	1.338		
medicate			.745	3.159	1.083	2.823
phone	-.455	-3.371	-.783	-3.217	-1.503	-4.007
mobility	.513	2.641	.911	3.586	1.166	2.454
hospital	.290	3.989	.344	2.888	.677	3.921
_cons	-4.407	-8.333	-4.623	-5.289	-7.276	-5.374
OBS.	1871		1329		636	

b. Unrestricted Health Status Models

VARIABLE	POOLED DATA (MODEL 4) COEFFICIENT	t	< 40 days from HSF to NHC (MODEL 5) COEFFICIENT	t	PORTLAND ONLY (MODEL 6) COEFFICIENT	t
age	.046	6.502	.024	2.000	.065	3.326
adlscore	.310	6.314	.554	8.785	.791	6.881
money	.363	2.971	.428	1.807	1.100	2.796
medicate			.838	3.312	1.221	2.831
phone	-.273	-2.060	-.651	-2.578	-1.265	-3.003
walking	.419	2.097	.775	2.936	1.007	2.001
hospital	.168	2.198			.432	2.138
cancer	.591	2.649	.489	1.409	.757	1.432
ostomy	.909	2.208	1.229	2.197	1.040	1.317
wheel	.343	1.686	.424	1.582	1.448	2.588
walker	.405	2.447	.619	2.564	1.162	2.569
cane	.293	2.546			.498	1.606
grab bar	.339	2.318	.587	2.653	.637	1.821
bench	.377	2.445	.697	3.096		
hoyerlift	-1.353	-3.078	-.814	-1.565	-3.045	-3.077
commode					.914	1.679
health	.247	3.579	.511	4.382	.831	4.352
_cons	-5.276	-8.670	-6.229	-6.149	-10.629	-6.173

Definition of Models

A. Models using ADL/IADL variables and prior hospitalization

Model 1: Uses pooled data from 4 sites with no restriction on the time between HSF and CAF

Model 2: Uses pooled data from 4 sites with cases having time between HSF & CAF <40 days.

Model 3: Uses Portland data with time between HSF & CAF < 40 days

B. Model using other health status variables

Model 4: Uses pooled data from 4 sites with no restriction on the time between HSF and CAF

Model 5: Uses pooled data from 4 sites with cases having time between HSF & CAF <40 days.

Model 6: Uses Portland data with time between HSF & CAF < 40 days

Examining these models, we note that the number of ADL limitations (as denoted by the variable adlscore) is the single most significant variable in each of the six logit models. Other variables that contribute significantly to NHC are: mobility limitations, the number of prior hospitalizations in the past 12 months and the need for assistance in taking medications.

A somewhat curious finding is the negative coefficient of the variable indicating that the person needs help in using the telephone. This finding was consistent in all six of the logit equations.

Among the variables added in the detailed models (Models 4 - 6), the two that were the most consistently significant predictors of NHC were poorer self-reported health status (excellent, good, fair or poor) and use of a walker.

In evaluating these models, we used a Pseudo-R^2 and the area under the ROC curve to determine the goodness of fit. We also compared the percent of correct classifications for probabilities less than and greater than .5. The comparisons of fit are shown in Table 4.

TABLE 5: Comparison of Goodness of Fit of Logit Models to Predict NHC

Model	Failures Pr <.5 Total	NonNHC	%NonNHC	Successes Pr>= .5 Total	NHC	%NHC	R^2	Area Under ROC
ADL/IADL Models:								
MODEL 1	1307	901	68.9	564	386	68.4	.18	.76
MODEL 2	1173	1039	88.6	164	116	70.7	.37	.89
MODEL 3	503	453	90.0	133	110	82.8	.50	.92
Unrestricted Health Status Models:								
MODEL 4	1366	923	67.6	505	349	69.11	.14	.73
MODEL 5	1161	1024	88.2	168	113	67.26	.33	.87
MODEL 6	524	458	87.4	112	94	83.93	.43	.89

Definition of Models
A. Models using ADL/IADL variables and prior hospitalization
Model 1: Uses pooled data from 4 sites with no restriction on the time between HSF and CAF
Model 2: Uses pooled data from 4 sites with cases having time between HSF & CAF <41 days.
Model 3: Uses Portland data with time between HSF & CAF < 41 days
B. Model using other health status variables
Model 4: Uses pooled data from 4 sites with no restriction on the time between HSF and CAF
Model 5: Uses pooled data from 4 sites with cases having time between HSF & CAF <41 days.
Model 6: Uses Portland data with time between HSF & CAF < 41 days

A comparison of the goodness of fit of these equations as shown in Table 5 indicates the following:

(1) A substantially better fit (as determined by R^2 and by the area under the ROC curve) is obtained by excluding cases having their NHC determination more than 40 days after their HSF. This can be seen by comparing Model 2 with Model 1 and Model 5 with Model 4. The 40-day limitation results in a Pseudo-R^2 value that is twice as high as when this limitation is removed and an area under the ROC curve that is nearly 20% higher.

(2) A substantially better fit (as determined by the pseudo R^2) is obtained by using the Kaiser-specific model instead of the all-site model, with the Pseudo-R^2 increased by 30% or more in both cases (Model 3 compared with Model 2; Model 6 compared with Model 5). The data suggests strongly that different models of NHC are used at the different sites (and therefore, in different States); for this reason, models based upon one sites data alone fit the data much better than do models based upon pooled data from the four sites.

(3) A model's fit is only moderately improved by including more detailed variables (Model 1, 2, and 3 compared with Models 4, 5, and 6 respectively.

(4) Overall, the models were able to correctly classify 88-90% of those who would not be nursing home certifiable (based upon a probability < .5) , while they were able to classify 67-83% of those who would be certifiable (based upon a probability > .5). The models, overall, seem to predict those who would not be NHC better than those who would be. The only case in which the two types of errors were comparable was in Models 4 and 6 - the Portland - only models. In this respect, in addition to the higher Pseudo-R^2 value as mentioned in (2) above, the fit for the Portland-only models were significantly better than the pooled-data models.

As a result of this analysis, (in support of earlier results indicating the poor agreement between HSF and CAF data when the time between HSF and NHC determination exceeded 40 days) we dropped Models 1 and 4 from further consideration.

5. Medicare cost analysis

a. NHC models

(1) Estimate of Medicare cost ratio and proportion of persons who are NHC

In examining Medicare costs, we used the logit models described in the previous section to determine the probability that a person was NHC. We evaluated this probability for each person included in NLTCS. Using these probabilities, we can estimate:

(1) the Medicare cost ratio C_{NHC} for the NHC population, i.e., the ratio of the mean value of Medicare costs for the NHC-individual and average Medicare costs.

(2) the proportion of persons p_{NHC} among the NHC population who are NHC. This proportion provides an estimate of the proportion of the U.S. population that are NHC

These mean values are determined by using the logit function as a weighting function, i.e.,

Equation 3) $C_{NHC} = [\text{Sum } f_i \times (nlivwt_i \times \quad c_i] / \text{ Sum } nlivwt_i$
$p_{NHC} = [\text{Sum } f_i \times nlivwt_i] / \text{ Sum } nlivwt_i$

where f_i is the predicted probability of being NHC for the i'th person, $nlivwt_i$ is the sample weight from NLTCS for the i'th person, c_i is the ratio of Medicare costs for the i'th person and average per capita Medicare costs, and the sum is carried out over all persons included in NLTCS.

To estimate the cost ratio C, the most straight-forward approach would be to use Model 2 - the model using pooled data from the four sites using only ADL/IADL and prior hospital use variables. We will use this estimate as the standard - there doesn't appear to be sufficient improvement in the fit gained by adding the additional health status variables (as in Model 5), and the use of one State's data (as in Models 3 and 6) would create a bias in the cost estimate of the NHC population. However, we will examine the implications of Models 3, 5, and 6 in addition to those found using Model 2 order to test the sensitivity of our results to differences in the type of NHC model selected.

In Table 6, we show estimates for the Medicare cost ratio C_{NHC} and the corresponding estimate for the proportion of persons p_{NHC} in the U.S. population that are NHC that are obtained from these models.

Table 6: Estimate of Medicare Cost Ratio and Proportion of the U.S. Population that are NHC Using ADL/IADL Predictive NHC Model with Pooled Data

Item	Value
C_{NHC}	3.17
p_{NHC}	4.95%

According to these estimates, nearly 5% of the U.S. 65+ population is NHC. Thus, the number of elderly persons who are NHC is close to the number who reside in nursing homes. Also, Medicare costs are more than 3 times higher for this population than the average among all elderly.

(2) Sensitivity Analysis

To examine the sensitivity of the model estimates of costs and NHC proportions, we examine how these estimates change when different assumptions are used. We consider the influence on C and p of the following:

- using the unrestricted health status model with pooled data (Model 5) for predicting NHC

- using Portland-only data for predicting NHC (Models 3 and 6).

In addition to examining the sensitivity with regard to model selection, we will also examine a second type of sensitivity. We note that the wording of the ADL questions on the Social/HMO HSF (i.e., the variables used to develop the predictive model for NHC) is not the same as the wording in the National Long-Term Care Survey. In developing Medicare cost estimates using NLTCS, we need to select whether the HSF item "needs some help" in ADL corresponds to the need for "assistance" or "supervision", which are the distinctions made on the NLTCS.

Table 7 provides a comparison of the Medicare cost ratio and proportion NHC for each of eight different models.

Table 7: Sensitivity of Medicare Cost Ratio and Proportion NHC to Model Specification and ADL Definition

Type of Model	Medicare Cost Ratio C_{NHC}	Proportion NHC in U.S. 65+ population P_{NHC}
1. ADL limitations interpreted as hands-on assistance		
ADL/IADL models		
Pooled data* (Model 2)	3.17	4.95%
Portland data (Model 3)	2.88	7.20%
Unrestricted health status models		
Pooled data (Model 5)	2.87	4.84%
Portland data (Model 6)	2.69	6.80%
2. ADL limitations interpeted as supervision or assistance		
ADL/IADL models		
Pooled data (Model 2)	2.80	5.59%
Portland data (Model 3)	2.63	7.59%
Unrestricted health status models		
Pooled data (Model 5)	2.95	5.93%
Portland data (Model 6)	2.73	8.17%

*Standard model as shown in Table 6

The data in Table 7 shows that the Medicare cost ratios range from a low of 2.80 (Model 2 with ADL defined as "supervision or assistance") to a high of 3.17 (Model 2 with ADL defined as "assistance") when the pooled U.S. data are used. Also, the proportion NHC varies from 4.95% to 5.93%.

We conclude that the cost ratios and NHC proportions are fairly stable under varying assumptions about how NHC is determined, as long as pooled data are used in developing the models.

We also find that the differences in cost ratios between the models using Portland data and the corresponding model using pooled data are small: Portland-based models lead to cost ratios that are between 6 and 9% less than those based upon pooled data. On the other hand, the Portland-only models lead to estimates of the size of the national NHC population considerably greater (by 36% - 46%) than those obtained from the pooled data.

We conclude that there are systematic differences in NHC definitions as defined by differrent states. Our analysis shows that these differences would lead to only slightly different estimates of cost ratios for the frail population, but substantially different estimates of the number of persons who are NHC.

b. Functional status models

In this section we examine alternative formulations of disability models that can be used as payment models for Medicare costs for the long-term care population.

As an initial step, we used multiple regression analysis to model costs employing selected demographic and disability variables. We use independent variables that were found to be significant in our earlier study (Gruenberg, et.al., 1990). The dependent variable in this analysis was the Medicare cost-ratio, i.e., the ratio between the individual's total Medicare costs for the year and the average of all persons. In this analysis we include all persons residing in the community.

The first multiple regression includes the independent variables shown in Table 8. The regression results are shown in Table 9.

Table 8: Description of Variables Used in Functional Status Models

Variable	Description
Age	age - 65
Sex	0=female, 1=male
Welfare	0=no, 1=yes
Adl	0=no limitations, 1-5 # of limitations
Meals	0=no disability 1=has disability (requires human assistance)
Grocery	0=no disability 1=has disability (" " ")
Medication	0=no disability 1=has disability (" " ")
Laundry	0=no disability 1=has disability (" " ")
Finance	0=no disability 1=has disability (" " ")
Phone	0=no disability 1=has disability (" " ")
Mobility	0=can go outside house 1=cannot go outside house (requires human assistance)
Mental	0=if less than 4 wrong MSQs 1=4 or more wrong MSQs
Onset	0=no ADL limitation 1=most recent occurrence over 5 years ago 2=less than 5 years to 1 year 3=less than 1 year to 6 months 4=less than 6 months to 3 months 5=less than 3 months

Table 9: Regression Equation for Medicare Cost Ratio Using All IADL Variables In Addition to Demographic, ADL Onset, and Mental Status.

Number of obs	=	19454
F(13, 19440)	=	79.30
Prob > F	=	0.0000
R-square	=	0.0504
Adj R-square	=	0.0497
Root MSE	=	2.6211

cost ratio	Coef.	Std. Err.	t	P>|t|	Beta
age(age-65)	.0191313	.0030706	6.231	0.000	.0463572
sex 0=f, 1=m	.2629416	.0386871	6.797	0.000	.0480783
welfare 0=n 1=y	.1531005	.0747444	2.048	0.041	.0146392
adls 0-5	.1720479	.0567633	3.031	0.002	.038824
meals	-.0470031	.1374292	-0.342	0.732	-.0039852
grocery	.4544881	.1023511	4.440	0.000	.0526515
medication	.4413952	.1281591	3.444	0.000	.0348739
laundry	.2285718	.1173152	1.948	0.051	.0228647
finance	-.246701	.0980589	-2.516	0.012	-.0254135
phone	-.689298	.1399187	-4.926	0.000	-.044423
mobility	.4204988	.0836184	5.029	0.000	.0519671
mental	-.219467	.1121778	-1.956	0.050	-.0156389
adl onset	.4248925	.0468677	9.066	0.000	.1043157
_constant	.5272861	.0360333	14.633	0.000	

The regression model explains 5% of the variance in cost Holding all other variables constant we observe that a 65-year old woman without any ADL or IADL problem, with no welfare incurs a cost ratio of .52. We observe that some variables are predictive of high costs. The variable onset has the greatest influence on cost as judged by its beta coefficient. Among other strongly related variables are grocery, mobility, sex, age, adl limitations and medications. Finance, phone and mental impairments have moderate negative influences, while meals does not have a significant relationship to cost (We adopted a .20 as our level of significance).

To make the results of the regression more graphic, we show in Table 10, the mean cost ratios for certain subgroups. For instance, those on welfare have higher mean costs than those who are not. Recency of onset generally, is indicative of higher costs. Comparison of groups 5 and 6 shows that having greater than 2 ADLs in itself incurs more costs than not having them irrespective of the recency of onset. There is a substantial increase in costs for those having one or more of the positive IADLs as can be seen by comparing groups 6 and 7. Comparison of groups 6 and 10 shows that the presence of cognitive impairments is associated with lower costs.

Since our attempt here is to derive models of payment which were both objective and practical, it was not necessary or appropriate to include all those variables which were significant, in the regression. More importantly, it is necessary to select only those variables that reflect the risk for high costs on the one hand, and are objectively verifiable on the other. This means that we could leave out some variables that were in fact significantly related to cost. In deciding to leave out variables, we adopt the following criteria.

1. The capitation model had to be based on measures that can be confirmed at a reasonable cost.

Those measures which had an ambiguous or unverifiable relationship to costs, although they had an influence on costs, were not used in our models. The variable "onset" provides the good example of such decision making. This variable as defined above provides the best indicator of costs according to the regression model. However, we decided to leave that variable out of our models because of the practical difficulties that are involved in recording and verifying the accuracy of such data.

Table 10: Predicted Value of Cost Ratio for Various Profiles

Subgroup	< 80 yrs. old		80 yrs. old +	
	Female	Male	Female	Male
1. Non-welfare	0.76	1.00	1.36	1.49
2. Welfare	1.18	1.48	1.86	1.83
3. With 2 or more ADLs	3.26	3.58	3.39	3.65
4. With 2 or more ADLs & onset of ADL occuring < 1 year ago	3.8	4.15	3.97	4.21
5. With 2 or more ADLs & onset of ADL occurring 5 or more years ago	2.43	2.72	2.71	2.90
6. With < 2 ADLs & no impairments in shopping, taking medicine, laundry and mobility	0.66	0.90	0.9	1.15
7. With < 2 ADLs & impairments in shopping, taking medicine, laundry & mobility	2.57	2.74	2.82	2.92
8. With < 2 ADLs & impairments in shopping, taking medicine, laundry, mobility, managing money & meal preparation	2.07	2.33	2.50	2.60
9. With 2 or more ADLs & cognitive impairment	2.86	3.29	3.23	3.26
10. With 2 or more ADLs & no cognitive impairment	3.46	3.67	3.55	3.92

If one were to objectify this variable, it would be necessary to clinically verify each instance of onset of ADL limitations for each individual over a long period of time. Because of the practical difficulties one would encounter in using this variable in determining costs we left this variable out of our evaluation of costs.

2. Cost variations due to a particular variable had to represent individuals' true needs rather than configurations of health care delivery that may result as a consequence of individuals' having these disabilities.

For example, noting the negative coefficient of variable indicating cognitive impairment, wee decided not to use it in our payment formula because of the ambiguity involved in interpreting the nature of its relationship to costs. Do people with cognitive impairments cost less because they actually have less serious medical conditions or, is it possible that there are other intervening factors that distort the true relationship of costs to cognitive impairments ? Because of this uncertainty we left out cognitive impairments from our payment formula.

According to the criteria specified in (1) and (2) above, we dropped from our analysis the following: IADL limitations that were negatively related to costs (phone, finance), one variable that was not significantly related to cost, namely, meals, and cognitive impairment. The regression model without the omitted variables is presented in Table 11 below. The new model explains 10% less of the variation than the previous model (R^2=.045 instead of .050). According to this model, ADL limitations, mobility limitations, and inability to do grocery shopping have the greatest influence on cost in the absence of the onset variable.

In order to minimize the effect of variations in cost produced by the intercorrelations that exist among IADL variables, we created a single variable that indicated the number of (positively correlated with Medicare costs) IADLs for each individual. These include: grocery shopping, taking medications, doing laundry and needing help to go outside the house. The regression equation using this variable is shown in Table 12. The new IADL variable has a significant influence on costs. The cost ratio increases by 1.5 for persons with all 4 of these IADL limitations, all other things being equal.

Table 11: Regression Equation of Cost Ratio using Demographic Variables, IADL and ADL variables.

Number of obs =	19489
F(8, 19480) =	113.33
Prob > F =	0.0000
R-square =	0.0445
Adj R-square =	0.0441
Root MSE =	2.6357

cost ratio	Coef.	Std. Err.	t	P>|t|	Beta
age-65	.0167939	.0030615	5.485	0.000	.0406043
sex	.2495626	.0388035	6.431	0.000	.0455177
welfare	.1335147	.0749227	1.782	0.075	.0127308
adls 0-5	.4243824	.0419357	10.120	0.000	.0962879
grocery	.4006279	.0987391	4.057	0.000	.0464153
medication	.1669721	.1184297	1.410	0.159	.0132078
laundry	.1752457	.1091977	1.605	0.109	.0175398
mobility	.4763621	.0827279	5.758	0.000	.0588795
_cons	.5469555	.0360945	15.153	0.000	

Table 12: Regression Equation of Cost Ratio using the Redefined IADL variable, ADL variables and Demographic variables.

Number of obs	=19489
F(5, 19483)	=182.01
Prob > F	=0.0000
R-square	=0.0446
Adj R-square	=0.0444
Root MSE	=2.6353

cost ratio	Coef.	Std. Err.	t	P>|t|	Beta
age-65	.0169327	.0030557	5.541	0.000	.0409399
sex	.2441676	.0386745	6.313	0.000	.0445337
welfare	.1271115	.0748998	1.697	0.090	.0121202
adls 0 - 5	.4339197	.0380544	11.403	0.000	.0984518
positive iadls (0, 1, 2, 3+4)	.3749513	.0289658	12.945	0.000	.1172922
_cons	.5484223	.0360347	15.219	0.000	

We also wanted to examine the structure of cost models that result from excluding IADLs, since these data are much more difficult to collect and verify. The regression equation below (Table 13) shows that by not including IADL as a parameter approximately 20% of the explained variation is lost.

Table 13: Regression Equation of Cost Ratio without the IADL variable

Number of obs	=	19489
F(4, 19484)	=	184.04
Prob > F	=	0.0000
R-square	=	0.0364
Adj R-square	=	0.0362
Root MSE	=	2.6465

cost ratio	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age-65	.0272887	.0029617	9.214	0.000	.0214835	.0330939
sex	.2277467	.0388186	5.867	0.000	.151659	.3038345
welfare	.2619741	.074488	3.517	0.000	.1159712	.4079769
adls 0-5	.7130694	.0314881	22.646	0.000	.6513501	.7747887
_cons	.5479965	.0361884	15.143	0.000	.4770641	.6189289

According to regression equations 12 and 13 all variables - age, sex, welfare status, the number of ADL and the number of IADL limitations as defined here - are significant at the .20 level. However, using regression equations for payment purposes may not be administratively convenient. Alternatively, we used all these variables in deriving underwriting ratios for categories of persons denoted by our variables. The following section presents these results.

c. Modified AAPCC underwriting tables

Using the regression models, we derived underwriting tables analogous to AAPCC tables using different methods for defining disability. We used three different methods for separating the sample population into groups. In the first method, "impaired" was defined as having an ADL or IADL problem.[1] In the second method, the number of ADL limitations was used. In the third method, Nursing Home Certifiability (NHC) was used.

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[1] More specifically, the need for hands-on human assistance was used to classify persons as IADL/ADL dependent.

The structure of the AAPCC tables was dictated by findings obtained from other multiple regression analysis which are not shown here. For unimpaired persons, welfare status was found to have a significant effect on costs. However, for impaired persons (defined either as NHC or as IADL/ADL impaired) welfare status was not significant. For this reason, a somewhat abbreviated structure for the AAPCC tables is possible.

In the ADL and NHC models, there is one impaired column. In the IADL/ADL model there are two - the IADL and the ADL columns. The IADL column presents cost ratio variations with the number of IADL limitations for those with no ADL limitations. The ADL column presents cost ratio variations for those with ADL limitations irrespective of whether they have IADL limitations.

For persons in some of the "impaired" or "welfare" subgroups, it was found that costs were not significantly correlated with age. In these cases, we used a single underwriting factor for all ages. The underwriting tables thus have a different structure for unimpaired and impaired states. The results are shown in Tables 14, 15 and 16.

Table 14: Cost Ratios for the ADL-IADL Model

	COMMUNITY						INSTITUTIONAL	
	UNIMPAIRED		IMPAIRED					
			IADL Group		ADL Group			
Age	Non Welfare	Welfare	# of IADLs	Cost Ratio	# of ADLs	Cost Ratio	Age	Cost Ratio
a. Males								
65-69	0.73	1.09	1	1.44	1	2.12	65-69	1.67
70-74	0.93	1.09	2	1.82	2	2.56	70-74	1.67
75-79	1.07	1.09	3+	1.95	3	3.96	75-79	1.67
80-84	1.27	1.09			4+	3.96	80-84	1.67
85 +	1.27	1.09					85 +	1.67
N*	8,919	295		863		509		330
b. Females								
65-69	0.49	0.98	1	1.20	1	2.22	65-69	1.32
70-74	0.69	0.98	2	1.35	2	2.53	70-74	1.32
75-79	0.76	0.98	3+	2.18	3	3.55	75-79	1.32
80-84	0.95	0.98			4+	3.55	80-84	1.32
85 +	0.95	0.98					85 +	1.32
N*	11,691	823		1,842		932		918

* Weighted number of persons in the survey, in thousands

Table 15: Cost Ratios Using the ADL Model

	COMMUNITY				INSTITUTIONAL	
	UNIMPAIRED		IMPAIRED			
	Non Welfare	Welfare	# of	Cost		Cost
AGE	Cost Ratio		ADLs	Ratio	AGE	Ratio
a. Males						
65-69	.75	1.23	1	2.12	65-69	1.67
70-74	.99	1.23	2	2.56	70-74	1.67
75-79	1.16	1.23	3	3.96	75-79	1.67
80-84	1.36	1.23	4+	3.96	80-84	1.67
85 +	1.36	1.23			85+	1.67
N*	9,669	407		509		330
MEAN	.98	1.23		2.95		1.67
b. Females						
65-69	.55	1.10	1	2.22	65-69	1.32
70-74	.76	1.10	2	2.53	70-74	1.32
75-79	.85	1.10	3	3.55	75-79	1.32
80-84	1.07	1.10	4+	3.55	80-84	1.32
85 +	1.07	1.10			85+	1.32
N*	13,203	1,153		932		918
MEAN	.76	1.10		2.72		1.32

* Weighted number of persons in the survey, in thousands

Table 16: Cost Ratios Using the NHC Model

	COMMUNITY			INSTITUTIONAL
	UNIMPAIRED		IMPAIRED	
AGE	NON WELFARE	WELFARE	NHC	
a. Males				
65-69	.75	1.21	3.35	1.67
70-74	.99	1.21	3.35	1.67
75-79	1.16	1.21	3.35	1.67
80-84	1.30	1.21	3.35	1.67
85+	1.30	1.21	3.35	1.67
N*	9,722	424	439	330
MEAN	.97	1.21	3.35	1.67
b. Females				
65-69	.55	1.07	3.07	1.32
70-74	.77	1.07	3.07	1.32
75-79	.86	1.07	3.07	1.32
80-84	1.04	1.07	3.07	1.32
85+	1.04	1.07	3.07	1.32
N*	13,289	1,188	810	918
MEAN	.76	1.07	3.07	1.32

* Weighted number of persons in the survey, in thousands

6. Discussion of Options

In the previous sections, we developed estimates for several alternative capitation models that could be used in the Social/HMO. The question of which model is more favorable is, in part, a question of individual preferences. The authors of this report found that there were important differences between their own best judgment, and those expressed by readers of the first draft. The discussion presented below represent the authors' ideas, somewhat tempered by comments received from those who reviewed this report.

There are two questions that need to be addressed:

(a) What variables should be included in the S/HMO payment model, i.e., which of the three models considered should be selected, and

(b) Should a regression formula be used for payment purposes, or should a set of underwriting tables be used.

We have considered several methods of deriving payment models. It is necessary to critically evaluate each of the models we have derived using these methods.

The ADL-IADL model had the highest R-square (we didn't show the R-square value for the NHC models, but they are lower than for the ADL-IADL model.) The reason for this is that in both the ADL and NHC models, only a very small percent of the population (about 5%) are singled out for higher payment. In contrast, the ADL/IADL model takes account of variance in costs of a much larger proportion of elderly, namely, those with IADL limitations. The fact that the IADL variable is significant immediately leads to a higher R_2 in the ADL/IADL model than in the ADL-only model.

However, one major problem associated with this model is the amount of data that needs to be collected and verified at any particular time. Whereas the ADL model would only require a validation assessment of a small sample (approximately 5 percent) of the Social/HMO membership, the IADL model requires information about the moderately impaired elderly, comprising 15-20% of the population. Some process similar to what was undertaken in the National Long-Term Care Survey would need to be used to single out frail S/HMO members and verify their ADL and IADL status. Since a clinical assessment of the total population would be too costly for this purpose, it would be necessary to rely on self-reported data. This raises questions of validity. In fact, data collected on the HSF in at least one case (i.e., Elderplan) has been found to be significantly biased in the direction of underestimating the number of frail persons.

The ADL model, too, has its disadvantages. One serious concern in this regard is that this model does not take into account the variability in the health risks of the majority of the S/HMO membership, except in so far as those risks are correlated with age, sex and welfare.

We have already pointed out the disadvantages of using NHC as a measure of disability in payment models because of the tenuous nature of this measure. From a policy perspective, there is also the problem of equity attached to this measure. How equitable is it for the HMOs carrying the same case-mix, but located in different states to be paid different amounts? What effects will these regional incentives have on the distribution of these services nationally? Because of these problems we would not recommend this measure to be incorporated in a payment system, if the goal was to develop a system that will be

implemented nationally.

However, given the fact that this is a demonstration program to be implemented at only a few sites for a well-defined period, it may be that NHC status is good enough to continue using, especially since the differences in cost ratios between even the most extremely different NHC models did not differ by more than 20%, and in most cases the differences were less than 10% (See Table 7).

To recapitulate, we ascertained that ADL-IADL model explains a greater proportion of variance in Medicare costs than the NHC models. Within the ADL-IADL model, we observed that ADLs have higher cost ratios than IADLs. In terms of advantages, assessments based on ADLs allow the use of less data, the quality of which may be better since it is possible to verify this data through a clinical assessment. The ADL-IADL model requires a reliance on self-reported data, or, a verification procedure for a large sub-population that is likely to be expensive.

To us, the NHC model seems less satisfactory than the ADL model, but the NHC model does have the advantage of having been already implemented over the course of the current demonstration. If this model were to be selected, it would be advisable to use a modified set of AAPCC tables, since our results indicate significantly higher cost ratios for the NHC population than those that are currently used.

Although the ADL-IADL model is, to us, the best model to use in the long-run, there is a need for research to determine how these data can be reliably collected. Given the unknowns about the reliability of the data in the HSF, it would not seem pragmatic to require Social/HMO sites to live with a capitation rate based upon these data, unless some research was carried out first.

There also needs to be an examination of how the AAPCC formula can be appropriately standardized; until now, the methods for determining the AAPCC in a county have required a knowledge of the case-mix for each Medicare recipient in the county. If ADL and IADL measures are used, there would be a need to develop some method for estimate for estimating the distribution of these variables in each county. In fact, this problem also needs to be addressed if the NHC model is used, although until now, the problem has been ignored.

For all our models we feel that the regression approach is more straightforward to derive than the underwriting tables. However, the results are likely to be less transparent and more

mysterious to providers and for this reason, it may be preferrable to use underwriting tables.

The underwriting table offers an administratively more attractive method of payment mainly because of its simplicity, since unlike the regression result, it enables us to deal with a population that is divided into convenient categories. Furthermore, we do not lose much of the sensitivity that we obtain from the regression equation because much of the information contained in the equation is retained.

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